

Review Article

A Survey of Localization in Wireless Sensor Network

Long Cheng,¹ Chengdong Wu,¹ Yunzhou Zhang,¹ Hao Wu,² Mengxin Li,³ and Carsten Maple⁴

¹ College of Information Science and Engineering, Northeastern University, Shenyang 110819, China

² Faculty of Engineering, University of Sydney, Sydney, 2006 NSW, Australia

³ Faculty of Information and Control Engineering, Shenyang Jianzhu University, Shenyang 110168, China

⁴ Department of Computer Science and Technology, University of Bedfordshire, Luton LU1 3JU, UK

Correspondence should be addressed to Long Cheng, chenglong2000_0@yahoo.com.cn

Received 18 September 2012; Accepted 16 November 2012

Academic Editor: Wei Meng

Copyright © 2012 Long Cheng et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Localization is one of the key techniques in wireless sensor network. The location estimation methods can be classified into target/source localization and node self-localization. In target localization, we mainly introduce the energy-based method. Then we investigate the node self-localization methods. Since the widespread adoption of the wireless sensor network, the localization methods are different in various applications. And there are several challenges in some special scenarios. In this paper, we present a comprehensive survey of these challenges: localization in non-line-of-sight, node selection criteria for localization in energy-constrained network, scheduling the sensor node to optimize the tradeoff between localization performance and energy consumption, cooperative node localization, and localization algorithm in heterogeneous network. Finally, we introduce the evaluation criteria for localization in wireless sensor network.

1. Introduction

Due to the availability of such low energy cost sensors, microprocessor, and radio frequency circuitry for information transmission, there is a wide and rapid diffusion of wireless sensor network (WSN). Wireless sensor networks that consist of thousands of low-cost sensor nodes have been used in many promising applications such as health surveillance, battle field surveillance, and environmental monitoring. Localization is one of the most important subjects because the location information is typically useful for coverage, deployment, routing, location service, target tracking, and rescue [1]. Hence, location estimation is a significant technical challenge for the researchers. And localization is one of the key techniques in WSN.

The sensor nodes are randomly deployed by the vehicle robots or aircrafts. While the Global Positioning System (GPS) is one of the most popular positioning technologies which is widely accessible, the weakness of high cost and energy consuming makes it different to install in every node. In order to reduce the energy consumption and cost, only a few of nodes which are called beacon nodes contain the

GPS modules. The rest of nodes could obtain their locations through localization method. The process of estimating the unknown node position within the network is referred to as node self-localization. And WSN is composed of a large number of inexpensive nodes that are densely deployed in a region of interests to measure certain phenomenon. The primary objective is to determine the location of the target. As shown in Figure 1, we classify the localization method into target/source localization and node self-localization. And the target localization can be further classified into four categories: single-target localization in WSN, multiple-target localization in WSN, single-target localization in wireless binary sensor network (WBSN), and multiple-target localization in WBSN. And node self-localization can be classified into two categories: range-based localization and range-free localization. The former method uses the measured the distance/angle to estimate the location. And the latter method uses the connectivity or pattern matching method to estimate the location. We will present the localization method in some special scenarios and finally introduce the evaluation criteria for localization in WSN.

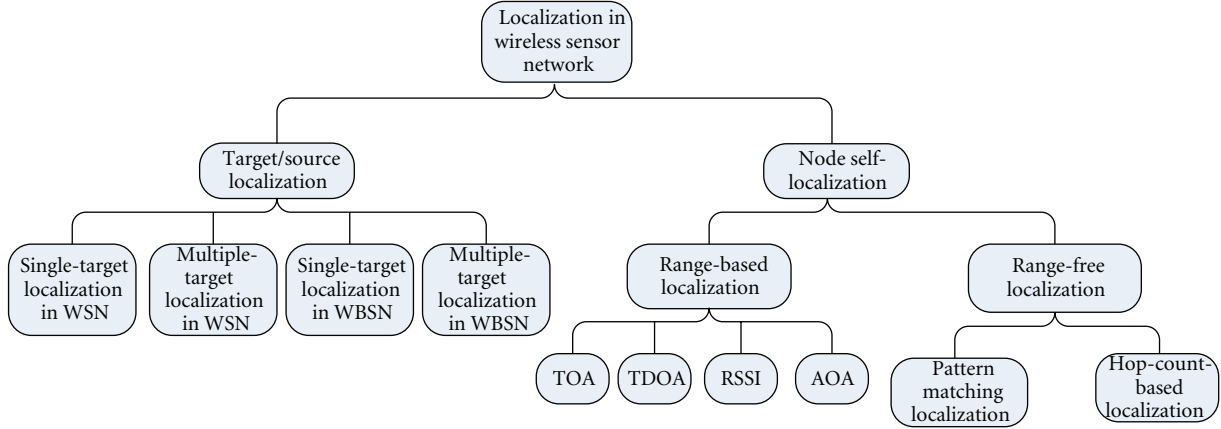


FIGURE 1: Localization methods taxonomy.

2. Target/Source Localization

2.1. Single-Target/Source Localization in Wireless Sensor Network. The source localization methods have a wide range of possible applications. The outdoor application includes vehicle or aircraft localization. In an indoor environment, this method could track the human speakers. In underwater environment, it can be used to locate the large sea animals and ships. There are several ways to estimate the source location: energy-based, angle of arrival (AOA) [2], time difference of arrival (TDOA) [3–6]. As an inexpensive approach, energy-based method is an attractive method because it requires low hardware configuration. In this survey, we focus on the energy-based source localization.

Single-source localization can be further divided into: energy decay model-based localization algorithm and model-independent localization algorithms.

(1) *Decay Model-Based Localization Algorithm.* Equation (1) shows the decay model in [7–9]. The received signal strength at i th sensor during time interval t can be written as

$$y_i(t) = g_i \frac{S(t)}{d_{ik}^2(t)} + n_i(t), \quad (1)$$

where g_i represents the gain factor of the i th sensor. We assume that $g_i = 1$. $S(t)$ is the signal energy at 1 meter away. And d_{ik} is the Euclidean distance between the i th sensor and the source. In addition n_i is the measurement noise modeled as zero mean white Gaussian with variance σ_i^2 , namely, $n_i \sim N(0, \sigma_i^2)$.

Although this energy decay model appears quite simplistic, it is the one commonly used in the literature. Since the objective function of single-source localization method has multiple local optima and saddle points [7], the authors formulated the problem as a convex feasibility problem and proposed a distributed version of the projection onto convex sets method. A weighted nonlinear least squares and weighted linear least squares methods [8] were proposed to estimate the location of the target. In [9], the authors

proposed normalized incremental subgradient algorithm to solve the energy-based sensor network source localization problem where the decay factor of the energy decay method is unknown.

Unlike the signal models in [7–9], the authors derived a more generalized statistical model [10] for energy observation. And a weighted direct/one-step least-squares-based algorithm was investigated to reduce the computational complexity. And in comparison with quadratic elimination method, these methods were amenable to a correction technique which incorporates the dependence of unknown parameters leading to further performance gains. This method offered a good balance between the localization performance and computational complexity. Energy ratio formulation [11] was an alternative approach that is independent of the source energy $S(t)$. This was accomplished by taking ratios of the energy reading of a pair of sensors in the noise-free case. In [12], the authors proposed an energy aware source localization method to reduce the energy consumption in localization.

(2) *Model-Independent Methods.* A kernel averaging approach [13] which needs not information about energy decay model was proposed. In [14], a novel model-independent localization method was proposed. Since the nodes with higher received signal strength measurement were closer to the source, a distributed sorting algorithm is employed. If the sensor nodes know their rank, the required distance estimates are obtained as the expected value of the respective probability density functions. Finally, the projection onto convex sets (POCS) method was used to estimate the location of the source.

2.2. Multiple-Target Localization in Wireless Sensor Network. Many works investigate the single-target localization. However, very limited papers investigate the multiple-target localization. Most of the works are based on the maximum likelihood estimator. The details of the maximum likelihood estimator are as follows.

The received signal strength at i th sensor during time interval t can be written as

$$y_i(t) = g_i \sum_{k=1}^K \frac{S_k(t)}{d_{ik}^\alpha(t)} + \varepsilon_i(t), \quad (2)$$

where $d_{ik}(t)$ is the distance between the i th sensor and the k th source. K is the number of the sources. g_i is the gain of i th sensor. $\varepsilon_i(t)$ is random variable with mean μ_i and variance σ_i^2 . $S_k(t)$ is the signal energy at 1 meter away for k th source. α is the attenuation exponent.

We define the following matrix notations as follows:

$$\begin{aligned} Y &= \left[\frac{y_1 - \mu_1}{\sigma_1}, \dots, \frac{y_N - \mu_N}{\sigma_N} \right]^T, \\ G &= \text{diag} \left[\frac{1}{\sigma_1}, \dots, \frac{1}{\sigma_N} \right], \\ S &= [S_1, S_2, \dots, S_K]^T, \\ D &= \begin{bmatrix} \frac{g_1}{d_{11}^2} & \frac{g_1}{d_{12}^2} & \dots & \frac{g_1}{d_{1K}^2} \\ \frac{g_2}{d_{21}^2} & \frac{g_2}{d_{22}^2} & \dots & \frac{g_2}{d_{2K}^2} \\ \vdots & \vdots & \dots & \vdots \\ \frac{g_N}{d_{N1}^2} & \frac{g_N}{d_{N2}^2} & \dots & \frac{g_N}{d_{NK}^2} \end{bmatrix}, \quad \varepsilon = [\varepsilon_1, \varepsilon_2, \dots, \varepsilon_N]^N. \end{aligned} \quad (3)$$

Using these notations, (2) can be represented as

$$Y = GDS + \varepsilon = HS + \varepsilon, \quad (4)$$

where $H = GD$.

So the joint probability density function (4) can be expressed as

$$f(Y | \theta) = (2\pi)^{-N/2} \exp \left(-\frac{1}{2} (Y - HS)^T (Y - HS) \right), \quad (5)$$

where $\theta = [r_1, r_2, \dots, r_K; S_1, S_2, \dots, S_K]^T$.

The maximum likelihood estimation is equivalent to minimizing the following function:

$$L(\theta) = (Y - HS)^T (Y - HS) = \|Y - HS\|^2. \quad (6)$$

We can obtain the maximum likelihood parameter estimation of θ by minimizing $L(\theta)$.

To minimize $L(\theta)$, we should take the following operation:

$$\frac{\partial L(\theta)}{\partial S_i} = 0. \quad (7)$$

This condition leads to the following relation:

$S = H^\nabla H$, where H^∇ is the pseudoinverse of the matrix H .

So we get the modified cost function:

$$\arg \min L'(\theta) = \|Y - HH^\nabla Y\|^2. \quad (8)$$

And a multiresolution (MR) search and the expectation maximization (EM) method [15] were proposed to solve (8). An efficient EM algorithm [16] was proposed to improve the estimation accuracy and avoid trapping into local optima through the effective sequential dominant-source initialization and incremental search schemes. An alternating projection [17] algorithm was proposed to decompose the multiple-source localization into a number of simpler, yet also nonconvex, optimization steps. This method could decrease the computation complexity.

2.3. Single-Target/Source Localization in Wireless Binary Sensor Network. Most of the source localization methods are focused on the measured signal strength; that is, the fusion center knows the measurements of the nodes. In order to obtain the measurements, the node needs the complex calculating process. The above methods require transmission of a large amount of data from sensors which may not be feasible under communication constraints. The binary sensors sense signals (infrared, acoustic, light, etc.) from their vicinity, and they only become active by transmitting a signal if the strength of the sensed signal is above a certain threshold. The binary sensor only makes a binary decision (detection or nondetection) regarding the measurement, and consequently, only its ID needs to be sent to the fusion center when it detects the target, otherwise it remains silent. So the binary sensor is a low-power and bandwidth-efficient solution for wireless sensor network.

Limited papers investigate the source localization in binary sensor network. And previous works have been proposed to try to estimate the location of the single source in wireless binary sensor network (WBSN). In [18], the authors proposed a maximum likelihood source location estimator in WBSN. A low complexity source localization method [19] which is based on the intersection of detection areas of sensors was introduced in noisy binary sensor networks. A subtract on negative add on positive (SNAP) [20] algorithm was proposed to identify the source location using the binary sensor networks. This is a fault-tolerant algorithm that is slightly less accurate but it is computationally less demanding in comparison with maximum likelihood estimation. In [21], the authors proposed a trust index based subtract on negative add on positive (TISNAP) method to improve the accuracy of localization for multiple event source localization. This algorithm reduces the impact of faulty nodes on the source localization by decreasing their trust index. And the TISNAP algorithm assumed that the distance between any two sources is far enough; that is, the node is influenced by only one source initially. So the localization process is similar to the single-source localization process. However, all of the previous works mainly focus on single-source localization. Fewer papers investigate the multiple-source localization in WBSN.

3. Node Self-Localization

3.1. Range-Based Localization. The classic methods to estimate the indoor location are time of arrival (TOA), time

difference of arrival (TDOA), angle of arrival (AOA), and received signal strength (RSS). TOA method measures travel times of signals between nodes. TDOA method locates by measuring the signals' arrival time difference between anchor nodes and unknown node. It is able to achieve high ranging accuracy, but requires extra hardware and consumes more energy. As an inexpensive approach, RSS has established the mathematical model on the basis of path loss attenuation with distance [22, 23], and it requires relatively low configuration and energy. We can obtain the distance between the beacon node and unknown node through the above three measurement methods. We set the position of beacon node is $\langle (x_1, y_1), \dots, (x_N, y_N) \rangle$ and the position of unknown node is $X = [x, y]^T$. \tilde{d}_i is the estimated distance between i th beacon node and unknown node. We can obtain the coordinate matrix of the unknown node as follows:

$$X = (A^T A)^{-1} A^T B, \quad (9)$$

$$A = 2 \begin{bmatrix} (x_1 - x_2) & (y_1 - y_2) \\ (x_1 - x_3) & (y_1 - y_3) \\ \vdots & \vdots \\ (x_1 - x_{N-1}) & (y_1 - y_{N-1}) \end{bmatrix},$$

$$B = \begin{bmatrix} \tilde{d}_2^2 - \tilde{d}_1^2 - (x_2^2 + y_2^2) + (x_1^2 + y_1^2) \\ \tilde{d}_3^2 - \tilde{d}_1^2 - (x_3^2 + y_3^2) + (x_1^2 + y_1^2) \\ \vdots \\ \tilde{d}_{N-1}^2 - \tilde{d}_1^2 - (x_{N-1}^2 + y_{N-1}^2) + (x_1^2 + y_1^2) \end{bmatrix}.$$

The angles between unknown node and a number of anchor nodes are used in the AOA method to estimate the location. This method needs the antenna array which is an expensive solution for low-cost sensor node.

3.2. Range-Free Localization

3.2.1. Hop-Count-Based Localization. As range-free positioning system, DV-Hop is the typical representation. It does not need to measure the absolute distance between the beacon node and unknown node. It uses the average hop distance to approximate the actual distances and reduces the hardware requirements. It is easy to implement and applicable to large network. But the positioning error is also correspondingly increased.

The positioning process of DV-Hop is divided into three stages: information broadcast, distance calculation, and position estimation. In information broadcast stage, the beacon nodes broadcast their location information package which includes hop count and is initialized to zero for their neighbors. The receiver records the minimal hop of each beacon nodes and ignores the larger hop for the same beacon nodes. Then the receiver increases the hop count by 1 and transmits it to neighbor nodes. All the nodes in a network can record the minimal hop counts of each beacon nodes. In distance calculation stage, according to the position of the beacon node and hop count, each beacon node uses the

following equation to estimate the actual distance of every hop:

$$\text{HopSize}_i = \frac{\sum_{j \neq i} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{j \neq i} h_j}, \quad (10)$$

where (x_i, y_i) and (x_j, y_j) are the coordinates of beacon nodes i and j , respectively. h_j is the hop count between the beacon nodes. Then, beacon nodes will calculate the average distance and broadcast the information to network. The unknown nodes only record the first average distance and then transmit it to neighbor nodes. Finally, the unknown node calculates its location through (9). In order to improve the localization accuracy, the improved algorithm mainly focuses on the following several aspects: average hop distance between beacon nodes, deployment of the beacon nodes, and node information.

(1) *Average Hop Distance between Beacon Nodes.* In the randomly deployed node density and connectivity network, Wang et al. [24] proposed a hop progress analytical model to estimate the optimal path distance between any pair of sensor nodes in the network. And it derived an expected hop progress and hop counts estimation method. A range-free localization algorithm (LAEP) which is using the trilateration techniques and the expected hop progress analytical results is proposed. Unlike the DV-Hop method, the LAEP broadcasts the anchor coordinated and the corresponding estimated distance to each sensor at the same time; therefore, it can dramatically reduce the network traffic and the communication delay. Wang only considers the node's receipt of beacon on a line to the utmost extent. Xu et al. [25] proposed a mobile anchor node localization method that is based on Archimedes curve. It takes communication path as curve spread. It avoids the error caused by large straight line dissemination and improves the precision. Lee et al. [26] proposed a robust weighted algorithm which is based on DV-Hop algorithm to calculate the average hop distances between unknown nodes and anchor nodes. It applies to most topological structure networks and reduces the location error. In the same way, Zhang et al. [27] improved the average hop distance based on minimum mean square error standard, which reduced positioning error. Lee et al. [28] used Karush-Kuhn-Tucker (KKT) standards and Lagrange's mean value theorem to correct the average hop distance error and improve location accuracy.

(2) *Deployment of the Beacon Nodes.* According to the ideal or regular node deployment scheme, the modified DV-Hop method is improved. Zheng et al. [29] firstly derived a beacon nodes deployment strategy that deploys a beacon node in the center of the area and other nodes are equally placed in the circle whose center is the center of the area and radius is half of the length of the area. Based on this deployment strategy, an accurate long-range DV-Hop algorithm is proposed. This method is adapted to large-scale network. Lee et al. [30] put forward a quadratic programming method to optimize

adjacent distance mapping. And it can be applied to the isotropic and anisotropic network.

(3) *Node Information*. Some modified methods were proposed through the neighbor node information such as anchor information and relationship between node and anchor or topology structure to improve the DV-Hop method. Zhong and He [31] proposed a proximity metric called RSD (regulated signature distance) to capture the distance relationships among 1-hop neighboring nodes. This method can be conveniently applied as a transparent supporting layer for state-of-the-art connectivity-based localization solutions to achieve better accuracy. He et al. [32] proposed a spring swarm localization algorithm (SSLA) which uses the network topology information and a small amount of anchor node location information to calculate unknown nodes position. Chen et al. [33] used the information of neighbor node to make anchor node communication range to be gradient to improve accuracy. Lim and Hou [34] addressed the issue of localization in anisotropic sensor networks. And a linear mapping method is proposed to characterize anisotropic features. It projects one embedding space built upon proximity measures into geographic distance space by using the truncated singular value decomposition (SVD) pseudoinverse technique. This method is different from MDS-Map method and owns higher accuracy than MDS-Map algorithm and the other expanded MDS-Map algorithm.

(4) *Comprehensive Improvement Method*. In addition to the above aspects, Brida et al. [35] used DV-Hop algorithm, DV-distance, DV-Euclidean algorithm, the constraint, and iteration condition that are to be added to select reference node. Then it used trilateration to find possible unknown node area, the estimated center of area as the final position. This algorithm could reduce the network energy consumption and improves localization accuracy. Chia-Ho [36] put forward a distributed, range-free localization algorithm. In this method, the mobile beacon node with directive antenna is used to supply the location information for the unknown node. Tan et al. [37] exploited acoustic communication to further research underwater range-free algorithm, especially proposing future prospect and development trend in view of the characteristic of underwater acoustic channel.

3.2.2. *Pattern Matching Method*. Pattern matching localization, also called map-based or Fingerprint algorithm, is one of the most viable solutions for range-free localization methods recently. The fingerprint localization involves two phases. During the first phase, the received signals at selected locations are recorded in an offline database called radio map. Then, the second phase, it works at the online state. The pattern matching algorithms are used to infer the location of unknown node by matching the current observed signal features to the prerecorded values on the map [38, 39].

Fang et al. [40] proposed a novel method to extract the feature of robust signals to efficiently mitigate the multipath effect. This method enhances the robustness under

a multipath fading condition and is commonly used for the indoor environments. Swangmuang and Krishnamurthy [41] presented a new analytical model that applies proximity graphs for approximating the probability distribution of error distance, which recorded a location fingerprint database by using the received signals. In addition, there are many problems under the indoor positioning environment as following: how to capture the character of propagation signal in the complex dynamic environment and how to accommodate the receiver gain difference of different mobile devices and so on. Wang et al. [42] solved these problems by modeling them as common mode noise and then developed a location algorithm based on a novel differential radio map. Gogolak et al. [43] proposed fingerprint localization methodology based on neural network which is applied in the real experimental indoor environment. It provided the necessary measurement results to the fingerprint localization.

4. Localization in Some Special Scenarios

Current and potential applications of sensor networks may be quite different. The scale of the network in these applications may be small or large, and the environments may be different. So the traditional localization methods are not suitable for the special scenarios. And there are some challenges for locating sensor nodes that need to be solved. In this survey, we mainly describe the following four challenges. The first challenge is NLOS (non-line-of-sight) ranging error problem. The direct path from the unknown node to the beacon is blocked by obstacles in wireless sensor network; the signal measurements include an error due to the excess path traveled because of the reflection of acoustic signal, which is termed as the NLOS error. The NLOS error results in the large location estimation error. The second challenge is the energy consumption and localization accuracy problem. Since the sensor node is powered by battery, the node may fail due to the depletion of energy. So the energy consumption is critical for the localization problem. It contains the node selection, tradeoff between localization performance and energy consumption, and node resource management. Since the unreliable hardware and complicate communication environment, the received information may be unreliable. Therefore, the third challenge is corporative localization. And the fourth challenge is the localization in heterogeneous sensor network.

4.1. Localization in NLOS Scenario

4.1.1. *NLOS Identification/Classification*. As shown in Figure 2, there may be no direct path from the beacon node to the unknown node in complicated environment. Because of the reflection and diffraction, the signal which is used for distance measurement can reflect and bound off multiple surfaces before arriving at the receiver. So the signal may actually travel excess path lengths and the direct path is blocked. The signal measurements include an error due to the excess path traveled which is termed as the NLOS error.

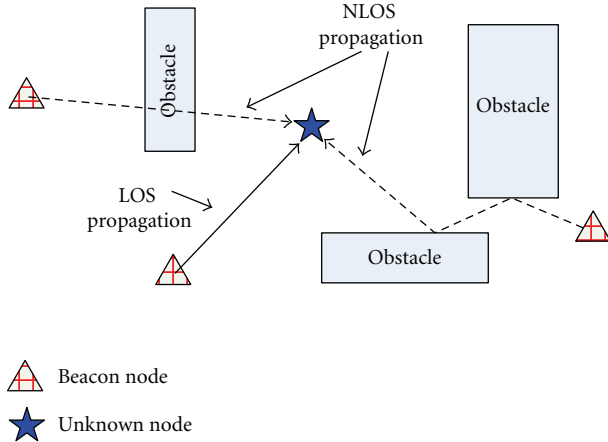


FIGURE 2: Example of localization in LOS/NLOS environments.

The NLOS problem has been studied in [44] and it was reported that the NLOS error was quite common in all environments except for rural areas. The large location estimation error will occur in NLOS environment. Accordingly, NLOS identification is particularly significant in localization. The problem of NLOS identification is essentially a detection problem. There are two main approaches to solve the NLOS errors: parametric methods and nonparametric methods. In this section, we give a brief overview of some key researches in this area.

Wylie and Holtzman [45] proposed a method based on parameter hypothesis test which determines the measurements whether belong to NLOS by comparing the NLOS variance with the LOS variance. It has a simple criterion but needs the detailed environment parameter and a prior knowledge. Borras et al. [46] investigated NLOS identification by using binary hypothesis test and generalized likelihood ratio for identifying NLOS error. It proposed a proper decision criteria and its premise is that the NLOS error is Gaussian distributed with a large variance. Based on Wylie-Holtzman algorithm, Mazuelas et al. [47] proposed an improvement by using NLOS ratio estimation and it will be able to correct the NLOS measurements from the previous knowledge of this ratio.

The aforementioned methods need a mount of priori knowledge and historical data. Chan et al. [48] proposed a residual test (RT) method to overcome the shortage which needs lots of priori knowledge. It determines the measurements whether belong to NLOS by measuring the samples appropriate to central Chi-distribution. The principle of this method is that if all measurements are LOS, and if the localization technique gives maximum likelihood estimates, then the residuals, normalized by the Cramer Rao Lower Bound (CRLB), will have a central χ^2 distribution. And if the measurements contain the NLOS error, the distribution is noncentral χ^2 distribution. Venkatraman and Caffery Jr. [49] investigated NLOS identification for moving targets by using a time series of range measurements. Gezici et al. [50] proposed a nonparameter-based hypothesis test method which used a distance metric between a known

measurement error distribution and a nonparametrically estimated distance measurement distribution. Yu and Guo [51] also proposed a nonparameter-based hypothesis test method by using generalized likelihood ratio to establish the relationship between LOS and NLOS. Then it used Neyman-Pearson (NP) test method for NLOS identification. A sequential probability ratio test [52] which is tolerant to the parameters fluctuations is employed to identify whether the measurement contains the non-line-of-sight (NLOS) errors.

4.1.2. NLOS Mitigation. Because of the existence of the non-ideal channel condition and non-line-of-sight transmission between the unknown nodes and beacon nodes, NLOS error mitigation has become a key technology and hotspot in the research about location estimation in wireless sensor network.

The first way attempts to identify the propagation conditions (LOS or NLOS) and then eliminate the measurements in NLOS; they only use the measurements in LOS to locate the unknown node. The propagation model-based method [53, 54] either directly employs the existing propagation models or empirically develops a model based on experimental results. The second way uses all NLOS and LOS measurements to estimate the location, but provides weighting or sealing to minimize the effects of the NLOS contributions. The weighting is determined by either the position geometry and beacon nodes layout or the residuals (fitting errors) of individual beacon node. The Taylor series linearization [55] (TS-LS), a widely used localization algorithm, should have the prior information of the error statistics which can be used to determine the weights. Chen [56] develops an algorithm to mitigate the NLOS errors by residual weighting when the range measurements corrupted by NLOS errors are not identifiable. The hypothesis testing [57] is employed to detect whether the environment is NLOS or LOS along with time of arrival (TOA) and received signal strength (RSS) measurements. And then an extended Kalman filter is used to nonlinear estimation.

In a scattering environment, most of the propagation paths between the unknown nodes and beacon nodes are NLOS; the constrained optimization techniques are used to reduce NLOS errors [58]. The neural network is employed to predict the NLOS error [59]; Kalman filters [60] and modified two-stage Kalman filter [61] are used to correct NLOS measurements.

All the positioning algorithms in NLOS environment focused more on the cellular network. These methods could be used in some scenarios for wireless sensor network localization. Fewer methods investigate the NLOS mitigation algorithm for Wireless sensor network.

4.2. Node Selection Criteria for Localization in Energy-Constrained Network. Due to the limited power of sensor node and hostile deployment environment, the node selection in WSN is different from the traditional node selection in traditional wireless network. If all the sensor nodes are used at the same time to executive localization

task without selection, although the energy consumption of nodes selection are saved, but at this time the repeatability of the received information would be quite larger. If the nodes are random selected to executive the localization task, the algorithm is simple and the extra overhead can be ignored, but localization accuracy is low in this case. Obviously, this method cannot satisfy the user's requirements for the accurate localization, the unbalance of energy consumption will appear, and some nodes may fail due to the depletion of energy. This may affect the network connectivity and may result in losing the sensed data. These characteristics of WSN determine selection method which is different from traditional network. Therefore, it is necessary to investigate nodes' selection mechanism in WSN.

The primary algorithm makes decision with global information [62]; this method minimized the expected filtered mean-squared position error for a given number of active nodes by using a global knowledge of all node locations. This algorithm needs the positions of nodes and broadcasts them to all nodes and a lot of data communication; therefore, it only can be applied to small networks. Based on the former algorithm, a local selection strategy is investigated [63]. This method determines whether or not that node should be active by only incorporating geometrical knowledge of itself and the active set of nodes from the previous information. Based on this approach, the researchers have also investigated other strategies, such as the least square method, Bayes probability method [64, 65]. Furthermore, in order to narrow the scope and scale of selected nodes, researchers proposed a method which combines the track and the current state of the robot. Zhang and Cao [66] proposed a multinode cooperation dynamic tree algorithm. This method ensured that spanning tree has low energy consumption and high information content by increasing and decreasing the number of the nodes dynamically. But this method still had some disadvantages: the root node needs data fusion and the new node needs to be calculated, and the consumption of energy is quite higher. Yang et al. [67] proposed online prediction based on particle filter and estimate the probability distribution of the target state under the Bayes framework. This method realized the optimal selection of the node sequence and introduced a shortest path algorithm to reduce the information transmission. Hamouda and Phillips [68] proposed a method which employs the moving speed of the mobile robot to improve the localization accuracy and consistency.

The signal shielding and multipath interference make the channel parameters become too complex to definite error factor. Bel et al. [69] proposed two selection principles to reduce the number of active nodes, and the nodes with accurate measured value (RSSI value larger than specified threshold) are selected. This method is effective to balance the accuracy and energy consumption and is suitable for the WSN which is hardware resource constrained. Zhao and Nehorai [70] used the Cramer-Rao equation to select the next node to participate in positioning. Because of the complexity of the observed model and the non-Gaussian noise, it is hard to get the optimal solution of the problem.

4.3. Scheduling the Sensor Node to Optimize the Tradeoff between Localization Performance and Energy Consumption.

A typical sensor network consists of a large number of small sensors which are deployed randomly. However, a sensor node has limited resources because of battery power and small memory. Therefore, nodes' resource management is compulsory. In typical sensor network applications, nodes are deployed in an unattended environment such as disaster management, habitat monitoring, industrial process control, and object tracking. Enormous event data will be generated for a long sensing time in WSN. Hence, by the methods of nodes resource management, effective usage of the vast amount of data is crucial. In the meanwhile, the scalability of both energy and spatial dimensions in distributed sensor network is a key issue. Sensor networks must track various phenomena at the same time and work within limited communication bandwidth, energy, and processing speed. Therefore, it is critical to distribute the workload across only the "relevant" sensors equally and leave other sensors available for other things. These characteristics of WSN determine the importance of nodes resource management.

Energy consumption is one of the most important issues in recent years. Ren and Meng [71] proposed a localization algorithm based on particle filtering for sensor networks. Assisted by multiple-transmit-power information, it outperforms the existing algorithms that do not utilize multiple-power information. You et al. [72] proposed a specified positional error tolerance, the sensor-enhanced and energy-efficient adaptive localization system in an application. This localization system dynamically sets sleep time for the nodes and adapting the sampling rate of target's mobility level. However, the process of error estimation dynamically relies on several factors in the specific environment. Gribben et al. [73] proposed a scheduling algorithm that selects a subset of active beacon nodes to be used in localization. It served to reduce the message overhead, increased network lifetime, and improved localization accuracy in dense mobile networks. However, maximizing the nodes' sleep time is much more energy efficient if the nodes never wake up until the reception of wake-up messages. The above algorithms have the same feature that the duty cycle of the sensor nodes is fixed in advance. In [74], the authors proposed an innovative probabilistic wake-up protocol for energy-efficient event detection in WSNs. The main idea of it is to reduce the duty cycle of every sensor via probabilistic wake-up through the dense deployment of sensor networks.

The problem of unique network localization and a mathematical topic known as rigidity theory have a strong connection. Goldenberg et al. [75] proposed a localization method for sparse networks by sweeping techniques. This method is saving all possible positions in each position step and pruning incompatible ones. One drawback of sweeping method is that the possible positions could increase exponentially as long as the number of nodes increased. Other types of localization methods are also available, such as using multidimensional scaling [76, 77] or mobile anchors [78, 79]. However, all the previous works tried to localize

more sensor nodes in a network without guaranteeing all of them. Khan et al. [80] introduced a localization method to localize all nodes by the minimal number of anchor nodes. However, they assume that the sensing range of each sensor can be enlarged to guarantee certain triangulation, so that three anchor nodes are enough to localize all sensors.

4.4. Cooperative Node Localization. There may be not enough information in the concentrated network or the node may contain the harmful information in sparse network. There are two branches in this area: (1) access the accuracy and reliability of the neighborhood nodes. (2) Improve precision with the cooperation of the active and passive nodes.

Some nodes may bring unreliable or even harmful information [81], so it is essential to review the received information. Tam et al. [82] employed the nearest link as reference to review the information. When there are massive link in dense network and positioning mainly depends on the geometry of the neighbor node topology information, the nearest neighbors may not correspond to the best link. Aiming at this issue, Denis et al. [83] proposed an adaptive method to eliminate the inefficient links, but this method has to work with neighbor node information, and the method cannot effectively reduce the number of packet effectively. Therefore, Das and Wymeersch [84] put forward a kind of distributed criterion; this method employed Cramer-Rao limit as identifiable parameters to identify the links. This method could avoid the invalid neighbor node links and unreliable transmission; thus, it can effectively reduce the computation time and the number of packets.

The accuracy of master-slave node cooperative localization is mainly depended on the measurements accuracy and the number of primary reference nodes (PRN, Primary Reference Node). But in the actual application, it is difficult to increase the number of primary reference nodes because of the factors of energy and the complexity. Wymeersch et al. [81] and Fujiwara et al. [85] put forward a new method: the nodes which received the information of the target and the primary reference nodes are termed as secondary reference nodes (SRN, secondary Reference Node), the SRNs participated in the localization in a passive way. This cooperative method reduced the required number of PRN with relatively higher localization accuracy. Gholami et al. [86] used the maximum likelihood estimation method to obtain the target position. The authors formulated the localization problem into finding the intersection of the vertex set by using geometry description. This method avoids getting into the local optimum.

4.5. Localization Algorithm in Heterogeneous Sensor Network. Most of the localization methods for the wireless sensor networks are only to consider the homogeneous network. The different kinds of the nodes such as the different maximum communication radius and the different nodes

own the different localization mechanisms are not considered in homogeneous, so the localization methods for the homogeneous network cannot be directly applied in the heterogeneous wireless sensor networks.

Du et al. [87] propose a new boundary nodes localization method by using a small number of anchor nodes. First the boundary nodes are elected and their positions are determined. Then the location information of boundary nodes is sent to other nodes through a small hop communication range. Finally, other nodes estimate their locations by the hop count and hop range. The scheme uses fewer beacon nodes, but has much smaller localization error and standard deviation. This method uses fewer beacon nodes, but with a smaller location error and standard deviation. Dong et al. [88] proposed a two-step localization method for two-tiered hierarchical heterogeneous sensor networks. The network consists of three types of nodes: anchor nodes with known locations, a few nodes equipped with both Ultrawide Band (UWB) and RF radios, and a large number of normal sensor nodes. The localization method works in two steps: firstly the high-accurate ranging capability of UWB nodes is used to estimate their location from a few anchor nodes, then, sensor nodes estimate their locations by using UWB nodes as anchor nodes.

Sometimes the distance between some nodes can be measured directly, while others cannot be. Selecting a different positioning algorithms accord to the mutual distance between nodes can be measured or not. Chiang et al. [89] proposed a hybrid unified Kalman tracking (HUKT) technique. The accuracy of tracking is based on both time of arrival (TOA) and time difference of arrival (TDOA) measurements. This method is proposed to adaptively adjust the weighting value between the TOA and TDOA measurements. The scheme can both provide higher localization accuracy for mobile network and adapt to environments with insufficient signal sources.

According to the different communication radius of the nodes, some super nodes can be deployed at some areas with plenty communication demands to transmit the information. Shen and Pesch [90] considered the nodes with more power and longer communication range as the heterogeneous nodes and propose a heuristic relay positioning algorithm for heterogeneous wireless sensor networks, to achieve the sharing of resources in heterogeneous wireless sensor network by using the relay nodes.

5. Evaluation Criteria for Localization in Wireless Sensor Network

The localization errors are inevitable in the estimations. In this section, we describe some common metrics: average localization error, root mean square error, and geometric mean error. And the Euclidean distance and Manhattan distance are two widely used metrics that are computed considering a two-dimensional coordinate system [91]. The Euclidean distance is defined to be the shortest distance between two coordinates. The Manhattan distance is defined to be the distance between two coordinates measured along

the axes at the right angles. The metrics are described as follows.

(1) *Average Localization Error.* The average localization error for Euclidean distance can be computed as follows:

$$\text{error} = \frac{1}{N_t} \sum_{i=1}^{N_t} \sqrt{(\hat{x}_i - x)^2 + (\hat{y}_i - y)^2}, \quad (11)$$

where N_t is the number of trails. (x, y) is the true location of the unknown node or source. (\hat{x}_i, \hat{y}_i) is the estimated location.

The average localization error for Manhattan distance can be computed as follows:

$$\text{error} = \frac{1}{N_t} \sum_{i=1}^{N_t} (|\hat{x}_i - x| + |\hat{y}_i - y|). \quad (12)$$

(2) *Root Mean Square Error.* The root mean square error for Euclidean distance can be computed as follows:

$$\text{error} = \sqrt{\frac{1}{N_t} \sum_{i=1}^{N_t} ((\hat{x}_i - x)^2 + (\hat{y}_i - y)^2)}. \quad (13)$$

The root mean square error for Manhattan distance can be computed as follows:

$$\text{error} = \sqrt{\frac{1}{N_t} \sum_{i=1}^{N_t} (|\hat{x}_i - x| + |\hat{y}_i - y|)}. \quad (14)$$

(3) *Geometric Mean Error.* The geometric mean error for Euclidean distance can be computed as follows:

$$\text{error} = \sqrt[N_t]{\prod_{i=1}^{N_t} ((\hat{x}_i - x)^2 + (\hat{y}_i - y)^2)}. \quad (15)$$

The geometric mean error for Manhattan distance can be computed as follows:

$$\text{error} = \sqrt[N_t]{\prod_{i=1}^{N_t} (|\hat{x}_i - x| + |\hat{y}_i - y|)}. \quad (16)$$

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant nos. 61203216, 61273078) and the Fundamental Research Fund for the Central Universities of China (N110404030, N110804004, and N110404004).

References

- [1] C. Wang and L. Xiao, "Sensor localization in concave environments," *ACM Transactions on Sensor Networks*, vol. 4, no. 1, article 3, 2008.
- [2] L. M. Kaplan, Q. Le, and P. Molnar, "Maximum likelihood methods for bearings-only target localization," in *Proceedings of IEEE International Conference on Acoustics, Speech, and Signal Processing*, vol. 5, pp. 3001–3004, Salt Lake City, Utah, USA, May 2001.
- [3] Y. Weng, W. Xiao, and L. Xie, "Total least squares method for robust source localization in sensor networks using TDOA measurements," *International Journal of Distributed Sensor Networks*, vol. 2011, Article ID 172902, 8 pages, 2011.
- [4] X. Qu and L. Xie, "Source localization by TDOA with random sensor position errors—part I: static sensors," in *Proceedings of the 15th International Conference on Information Fusion*, pp. 48–53, Singapore, July 2012.
- [5] X. Qu and L. Xie, "Source localization by TDOA with random sensor position errors—part II: mobile sensors," in *Proceedings of the 15th International Conference on Information Fusion*, pp. 54–59, Singapore, July 2012.
- [6] K. C. Ho, "Bias reduction for an explicit solution of source localization using TDOA," *IEEE Transactions on Signal Processing*, vol. 60, no. 5, pp. 2101–2114, 2012.
- [7] D. Blatt and A. O. Hero, "Energy-based sensor network source localization via projection onto convex sets," *IEEE Transactions on Signal Processing*, vol. 54, no. 9, pp. 3614–3619, 2006.
- [8] K. Deng and Z. Liu, "Weighted least-squares solutions of energy-based collaborative source localization using acoustic array," *International Journal of Computer Science and Network Security*, vol. 7, no. 1, pp. 159–165, 2007.
- [9] Q. Shi and C. He, "A new incremental optimization algorithm for ML-based source localization in sensor networks," *IEEE Signal Processing Letters*, vol. 15, pp. 45–48, 2008.
- [10] C. Meesookho, U. Mitra, and S. Narayanan, "On energy-based acoustic source localization for sensor networks," *IEEE Transactions on Signal Processing*, vol. 56, no. 1, pp. 365–377, 2008.
- [11] D. Li and Y. H. Hu, "Energy-based collaborative source localization using acoustic microsensor array," *EURASIP Journal on Advances in Signal Processing*, vol. 2003, article 985029, 2003.
- [12] E. Maşazade, R. Niu, P. K. Varshney, and M. Keskinöz, "Energy aware iterative source localization for wireless sensor networks," *IEEE Transactions on Signal Processing*, vol. 58, no. 9, pp. 4824–4835, 2010.
- [13] M. G. Rabbat, R. D. Nowak, and J. Bucklew, "Robust decentralized source localization via averaging," in *Proceedings of IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP '05)*, vol. 5, pp. V1057–V1060, Philadelphia, Pa, USA, March 2005.
- [14] D. Ampeliotis and K. Berberidis, "Energy-based model-independent source localization in wireless sensor networks," in *Proceedings of the 16th European Signal Processing Conference*, Lausanne, Switzerland, August 2008.
- [15] X. Sheng and Y. H. Hu, "Maximum likelihood multiple-source localization using acoustic energy measurements with wireless sensor networks," *IEEE Transactions on Signal Processing*, vol. 53, no. 1, pp. 44–53, 2005.
- [16] W. Meng, W. Xiao, and L. Xie, "An efficient EM algorithm for energy-based multisource localization in wireless sensor networks," *IEEE Transactions on Instrumentation and Measurement*, vol. 60, no. 3, pp. 1017–1027, 2011.
- [17] D. Ampeliotis and K. Berberidis, "Low complexity multiple acoustic source localization in sensor networks based on energy measurements," *Signal Processing*, vol. 90, no. 4, pp. 1300–1312, 2010.

- [18] R. Niu and P. Varshney, "Target location estimation in wireless sensor networks using binary data," in *Proceedings of the 38th International Conference on Information Sciences and Systems*, pp. 17–19, Princeton, NJ, USA, March 2004.
- [19] X. Liu, G. Zhao, and X. Ma, "Target localization and tracking in noisy binary sensor networks with known spatial topology," *Wireless Communications and Mobile Computing*, vol. 9, no. 8, pp. 1028–1039, 2009.
- [20] M. P. Michaelides and C. G. Panayiotou, "SNAP: fault tolerant event location estimation in sensor networks using binary data," *IEEE Transactions on Computers*, vol. 58, no. 9, pp. 1185–1197, 2009.
- [21] X. Xu, X. Gao, J. Wan, and N. Xiong, "Trust index based fault tolerant multiple event localization algorithm for WSNs," *Sensors*, vol. 11, no. 7, pp. 6555–6574, 2011.
- [22] K. Lu, X. Xiang, D. Zhang, R. Mao, and Y. Feng, "Localization algorithm based on maximum a posteriori in wireless sensor networks," *International Journal of Distributed Sensor Networks*, vol. 2012, Article ID 260302, 7 pages, 2012.
- [23] L. Cheng, C. D. Wu, Y. Z. Zhang, and Y. Wang, "Indoor robot localization based on wireless sensor networks," *IEEE Transactions on Consumer Electronics*, vol. 57, no. 3, pp. 1099–1104, 2011.
- [24] Y. Wang, X. Wang, D. Wang, and D. P. Agrawal, "Range-free localization using expected hop progress in wireless sensor networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 20, no. 10, pp. 1540–1552, 2009.
- [25] H. Xu, Y. Tu, W. Xiao, Y. Mao, and T. Shen, "An archimedes curve-based mobile anchor node localization algorithm in wireless sensor networks," in *Proceedings of the 8th World Congress on Intelligent Control and Automation (WCICA '10)*, pp. 6993–6997, Jinan, China, July 2010.
- [26] J. Lee, W. Chung, and E. Kim, "Robust DV-Hop algorithm for localization in wireless sensor network," in *Proceedings of the International Conference on Control, Automation and Systems*, pp. 2506–2509, Gyeonggi-do, South Korea, October 2010.
- [27] J. Zhang, W. Li, D. Cui, X. Sun, and F. Zhou, "Study on improved DV-Hop node localization algorithm in wireless sensor network," in *Proceedings of the 5th IEEE Conference on Industrial Electronics and Applications (ICIEA '10)*, pp. 1855–1858, Taichung, Taiwan, June 2010.
- [28] S. W. Lee, D. Y. Lee, and C. W. Lee, "Enhanced DV-Hop algorithm with reduced hop-size error in ad hoc networks," *IEICE Transactions on Communications*, vol. 94, no. 7, pp. 2130–2132, 2011.
- [29] Y. Zheng, L. Wan, Z. Sun, and S. Mei, "A long range DV-Hop localization algorithm with placement strategy in wireless sensor networks," in *Proceedings of the 4th International Conference on Wireless Communications, Networking and Mobile Computing (WiCOM '08)*, Dalian, China, October 2008.
- [30] J. Lee, W. Chung, and E. Kim, "A new range-free localization method using quadratic programming," *Computer Communications*, vol. 34, no. 8, pp. 998–1010, 2011.
- [31] Z. Zhong and T. He, "RSD: a metric for achieving range-free localization beyond connectivity," *IEEE Transactions on Parallel and Distributed Systems*, vol. 22, no. 11, pp. 1943–1951, 2011.
- [32] Q. B. He, F. Chen, S. Cai, J. Hao, and Z. Liu, "An efficient range-free localization algorithm for wireless sensor networks," *Science China Technological Sciences*, vol. 54, no. 5, pp. 1053–1060, 2011.
- [33] Y. Chen, W. Chung, and S. Yuan, "Order-based localization scheme for ad hoc sensor networks," in *Proceedings of the 73rd IEEE Vehicular Technology Conference*, pp. 1–5, Budapest, Hungary, May 2011.
- [34] H. Lim and J. C. Hou, "Distributed localization for anisotropic sensor networks," *ACM Transactions on Sensor Networks*, vol. 5, no. 2, article 11, 2009.
- [35] P. Brida, J. Machaj, and J. Duha, "A novel optimizing algorithm for DV based positioning methods in ad hoc networks," *Elektronika ir Elektrotechnika*, no. 1, pp. 33–38, 2010.
- [36] O. Chia-Ho, "A localization scheme for wireless sensor networks using mobile anchors with directional antennas," *IEEE Sensors Journal*, vol. 7, no. 11, pp. 1607–1616, 2011.
- [37] H. P. Tan, R. Diamant, and W. K. G. Seah, "A survey of techniques and challenges in underwater localization," *Ocean Engineering*, vol. 38, no. 14–15, pp. 1663–1676, 2011.
- [38] X. Luo, W. J. O'Brien, and C. L. Julien, "Comparative evaluation of Received Signal-Strength Index (RSSI) based indoor localization techniques for construction jobsites," *Advanced Engineering Informatics*, vol. 25, no. 2, pp. 355–363, 2011.
- [39] D. J. Suroso, P. Cherntanomwong, P. Sooraksa, and J. Takada, "Fingerprint-based technique for indoor localization in wireless sensor networks using Fuzzy C-Means clustering algorithm," in *Proceedings of the International Symposium on Intelligent Signal Processing and Communications Systems*, pp. 1–5, Chiang Mai, Thailand, December 2011.
- [40] S. H. Fang, T. N. Lin, and K.-C. Lee, "A novel algorithm for multipath fingerprinting in indoor WLAN environments," *IEEE Transactions on Wireless Communications*, vol. 7, no. 9, pp. 3579–3588, 2008.
- [41] N. Swangmuang and P. Krishnamurthy, "An effective location fingerprint model for wireless indoor localization," *Pervasive and Mobile Computing*, vol. 4, no. 6, pp. 836–850, 2008.
- [42] J. Wang, Q. Gao, H. Wang et al., "Differential radio map-based robust indoor localization," *EURASIP Journal on Wireless Communications and Networking*, vol. 2011, article 17, 2011.
- [43] L. Gogolak, S. Pletl, and D. Kukolj, "Indoor fingerprint localization in WSN environment based on neural network," in *Proceedings of the 9th IEEE International Symposium on Intelligent Systems and Informatics*, pp. 293–296, Subotica, Serbia, September 2011.
- [44] M. I. Silventoinen and T. Rantalainen, "Mobile station emergency locating in GSM," in *Proceedings of IEEE International Conference on Personal Wireless Communications*, pp. 232–238, New Delhi, India, February 1996.
- [45] M. P. Wylie and J. Holtzman, "The non-line of sight problem in mobile location estimation," in *Proceedings of the 5th IEEE International Conference on Universal Personal Communications Record (ICUPC '96)*, pp. 827–831, Cambridge, Mass, USA, October 1996.
- [46] J. Borras, P. Hatrack, and N. B. Mandayam, "Decision theoretic framework for NLOS identification," in *Proceedings of the 48th IEEE Vehicular Technology Conference (VTC '98)*, pp. 1583–1587, Ottawa, Canada, May 1998.
- [47] S. Mazuelas, F. A. Lago, J. Blas et al., "Prior NLOS measurement correction for positioning in cellular wireless networks," *IEEE Transactions on Vehicular Technology*, vol. 58, no. 5, pp. 2585–2591, 2009.
- [48] Y. T. Chan, W. Y. Tsui, H. C. So, and P. C. Ching, "Time-of-arrival based localization under NLOS conditions," *IEEE Transactions on Vehicular Technology*, vol. 55, no. 1, pp. 17–24, 2006.
- [49] S. Venkatraman and J. J. Caffery, "Statistical approach to non-line-of-sight BS identification," in *Proceedings of the*

- 5th International Symposium on Wireless Personal Multimedia Communications*, vol. 1, pp. 296–300, Honolulu, Hawaii, USA, October 2002.
- [50] S. Gezici, H. Kobayashi, and H. V. Poor, “Non-parametric non-line-of-sight identification,” in *Proceedings of the 58th IEEE Vehicular Technology Conference (VTC '03-Fall)*, vol. 4, pp. 2544–2548, Orlando, Fla, USA, October 2003.
 - [51] K. Yu and Y. J. Guo, “Statistical NLOS identification based on AOA, TOA, and signal strength,” *IEEE Transactions on Vehicular Technology*, vol. 58, no. 1, pp. 274–286, 2009.
 - [52] L. Cheng, C. D. Wu, Y. Z. Zhang, and Y. Wang, “An indoor localization strategy for mini-UAV in presence of obstacles,” *International Journal of Advanced Robotic Systems*, vol. 2012, pp. 1–8, 2012.
 - [53] S. Al-Jazzar, J. Caffery Jr., and H. R. You, “A scattering model based approach to NLOS mitigation in TOA location systems,” in *Proceedings of the 55th IEEE Vehicular Technology Conference*, pp. 861–865, Birmingham, Ala, USA, May 2002.
 - [54] L. Liu, P. Deng, and P. Fan, “A TOA reconstruction method based on ring of scatterers model,” in *Proceedings of the 4th International Conference on Parallel and Distributed Computing, Applications and Technologies (PDCAT '03)*, pp. 375–377, Chengdu, China, August 2003.
 - [55] W. H. Foy, “Position-location solutions by Taylor-series estimation,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 12, no. 2, pp. 187–194, 1976.
 - [56] P. C. Chen, “A non-line-of-sight error mitigation algorithm in location estimation,” in *Proceedings of IEEE Wireless Communications and Networking Conference*, vol. 1, pp. 316–320, New Orleans, La, USA, September 1999.
 - [57] L. Cheng, C. D. Wu, Y. Z. Zhang, and H. Chu, “Mobile location estimation scheme in NLOS environment,” *IEICE Electronics Express*, vol. 8, no. 21, pp. 1829–1835, 2011.
 - [58] S. Venkatraman, J. J. Caffery, and H. R. You, “Location using LOS range estimation in NLOS environments,” in *Proceedings of the 55th Vehicular Technology Conference*, pp. 856–860, Birmingham, Ala, USA, May 2002.
 - [59] I. Povescu, I. Nafomita, P. Constantinou, A. Kanatas, and N. Moraitis, “Neural networks applications for the prediction of propagation path loss in urban environments,” in *Proceedings of the 53rd IEEE Semi-Annual Vehicular Technology Conference*, pp. 387–391, Rhodes, Greece, May 2001.
 - [60] B. L. Le, K. Ahmed, and H. Tsuji, “Mobile location estimator with NLOS mitigation using Kalman filtering,” in *Proceedings of IEEE Wireless Communications and Networking (WCNC '03)*, vol. 3, pp. 1969–1973, New Orleans, La, USA, March 2003.
 - [61] W. Kim, G. I. Jee, and J. Lee, “Wireless location with NLOS error mitigation in Korean CDMA system,” in *Proceedings of the 2nd International Conference on 3G Mobile Communication Technologies*, pp. 134–138, London, UK, March 2001.
 - [62] L. M. Kaplan, “Global node selection for localization in a distributed sensor network,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 42, no. 1, pp. 113–135, 2006.
 - [63] L. M. Kaplan, “Local node selection for localization in a distributed sensor network,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 42, no. 1, pp. 136–146, 2006.
 - [64] A. Bel, J. L. Vicario, and G. Seco-Granados, “Node selection for cooperative localization: efficient energy vs. accuracy trade-off,” in *Proceedings of the 5th IEEE International Symposium on Wireless Pervasive Computing (ISWPC '10)*, pp. 307–312, Modena, Italy, May 2010.
 - [65] X. J. Yang, K. Y. Xing, K. L. Shi, and Q. Pan, “Dynamic collaborative algorithm for maneuvering target tracking in sensor networks,” *Acta Automatica Sinica*, vol. 33, no. 10, pp. 1029–1035, 2007.
 - [66] W. S. Zhang and G. H. Cao, “DCTC: dynamic convoy tree-based collaboration for target tracking in sensor networks,” *IEEE Transactions on Wireless Communications*, vol. 3, no. 5, pp. 1689–1701, 2004.
 - [67] X. J. Yang, K. Y. Xing, K. L. Shi, and Q. Pan, “Dynamic collaborative algorithm for maneuvering target tracking in sensor networks,” *Acta Automatica Sinica*, vol. 33, no. 10, pp. 1029–1035, 2007.
 - [68] Y. E. M. Hamouda and C. Phillips, “Metadata based optimal sensor selection for multi-target tracking in wireless sensor networks,” *International Journal of Research and Reviews in Computer Science*, vol. 2, no. 1, pp. 189–200, 2011.
 - [69] A. Bel, J. Lopez Vicario, and G. Seco-Granados, “Real-time path loss and node selection for cooperative localization in wireless sensor networks,” in *Proceedings of the 21st IEEE International Symposium on Personal, Indoor and Mobile Radio Communications Workshops (PIMRC '10)*, pp. 283–288, Istanbul, Turkey, September 2010.
 - [70] T. Zhao and A. Nehorai, “Information-driven distributed maximum likelihood estimation based on Gauss-Newton method in wireless sensor networks,” *IEEE Transactions on Signal Processing*, vol. 55, no. 9, pp. 4669–4682, 2007.
 - [71] H. Ren and M. Q. Meng, “Power adaptive localization algorithm for wireless sensor networks using particle filter,” *IEEE Transactions on Vehicular Technology*, vol. 58, no. 5, pp. 2498–2508, 2009.
 - [72] C. You, Y. Chen, J. Chiang, P. Huang, H. Chu, and S. Lau, “Sensor-enhanced mobility prediction for energy-efficient localization,” in *Proceedings of the 3rd Annual IEEE Conference on Sensor and Ad Hoc Communications and Networks*, vol. 1, pp. 565–574, Reston, Va, USA, September 2006.
 - [73] J. Gribben, A. Boukerche, and R. Pazzi, “Scheduling for scalable energy-efficient localization in mobile ad hoc networks,” in *Proceedings of the 7th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON '10)*, Boston, Mass, USA, June 2010.
 - [74] Y. Zhu and L. M. Ni, “Probabilistic wakeup: adaptive duty cycling for energy efficient event detection,” in *Proceedings of the 10th ACM Symposium on Modeling, Analysis, and Simulation of Wireless and Mobile Systems (MSWiM '07)*, pp. 360–367, Chania, Greece, October 2007.
 - [75] D. K. Goldenberg, P. Bihler, M. Cao et al., “Localization in sparse networks using sweeps,” in *Proceedings of the 12th Annual International Conference on Mobile Computing and Networking (MOBICOM '06)*, pp. 110–121, Los Angeles, Calif, USA, September 2006.
 - [76] X. Ji and H. Zha, “Sensor positioning in wireless ad-hoc sensor networks using multidimensional scaling,” in *Proceedings of the 23rd Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM '04)*, vol. 4, pp. 2652–2661, Hong Kong, China, March 2004.
 - [77] Y. Shang and W. Ruml, “Improved MDS-based localization,” in *Proceedings of the 23rd Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM '04)*, vol. 4, pp. 2640–2651, Hong Kong, China, March 2004.
 - [78] K.-F. Su, C.-H. Ou, and H. C. Jiau, “Localization with mobile anchor points in wireless sensor networks,” *IEEE Transactions on Vehicular Technology*, vol. 54, no. 3, pp. 1187–1197, 2005.
 - [79] M. Erol, L. F. M. Vieira, and M. Gerla, “Localization with Dive'n'Rise (DNR) beacons for underwater acoustic sensor

- networks,” in *Proceedings of the 2nd Workshop on Underwater Networks (WuWNet '07)*, pp. 97–100, Montreal, Canada, September 2007.
- [80] U. A. Khan, S. Kar, and J. M. F. Moura, “Distributed sensor localization in random environments using minimal number of anchor nodes,” *IEEE Transactions on Signal Processing*, vol. 57, no. 5, pp. 2000–2016, 2009.
 - [81] H. Wymeersch, J. Lien, and M. Z. Win, “Cooperative localization in wireless networks,” *Proceedings of the IEEE*, vol. 97, no. 2, pp. 427–450, 2009.
 - [82] V. Tam, K. Cheng, and K. Lui, “Using micro-genetic algorithms to improve localization in wireless sensor networks,” *Journal of Communications*, vol. 1, no. 4, pp. 1–10, 2006.
 - [83] B. Denis, M. Maman, and L. Ouvry, “On the scheduling of ranging and distributed positioning updates in cooperative IR-UWB networks,” in *Proceedings of IEEE International Conference on Ultra-Wideband (ICUWB '09)*, pp. 370–375, Vancouver, Canada, September 2009.
 - [84] K. Das and H. Wymeersch, “Censored cooperative positioning for dense wireless networks,” in *Proceedings of the 21st IEEE International Symposium on Personal, Indoor and Mobile Radio Communications Workshops (PIMRC '10)*, pp. 262–266, Istanbul, Turkey, September 2010.
 - [85] R. Fujiwara, K. Mizugaki, T. Nakagawa, D. Maeda, and M. Miyazaki, “TOA/TDOA hybrid relative positioning system using UWB-IR,” in *Proceedings of IEEE Radio and Wireless Symposium (RWS '09)*, pp. 679–682, San Diego, Calif, USA, January 2009.
 - [86] M. R. Gholami, S. Gezici, M. Rydström, and E. G. Ström, “A distributed positioning algorithm for cooperative active and passive sensors,” in *Proceedings of the 21st IEEE International Symposium on Personal Indoor and Mobile Radio Communications (PIMRC '10)*, pp. 1713–1718, Istanbul, Turkey, September 2010.
 - [87] X. Du, D. Mandala, W. Zhang, C. You, and Y. Xiao, “A boundary-node based localization scheme for heterogeneous wireless sensor networks,” in *Proceedings of IEEE Military Communications Conference (MILCOM '07)*, pp. 1–7, Orlando, Fla, USA, October 2007.
 - [88] S. Dong, P. Agrawal, and K. Sivalingam, “Localization error evaluation in heterogeneous sensor networks,” in *Proceedings of IEEE Global Telecommunications Conference*, pp. 1–5, New Orleans, La, USA, December 2008.
 - [89] C. T. Chiang, P. H. Tseng, and K. T. Feng, “Hybrid unified kalman tracking algorithms for heterogeneous wireless localization systems,” *IEEE Transactions on Vehicular Technology*, vol. 61, no. 2, pp. 702–715, 2012.
 - [90] C. Shen and D. Pesch, “A heuristic relay positioning algorithm for heterogeneous wireless networks,” in *Proceedings of the 69th IEEE Vehicular Technology Conference*, pp. 1–5, Barcelona, Spain, April 2009.
 - [91] H. Aksu, D. Aksoy, and I. Korpeoglu, “A study of localization metrics: evaluation of position errors in wireless sensor networks,” *Computer Networks*, vol. 55, no. 15, pp. 3562–3577, 2011.